Aus dem Institut für Klinische Radiologie
der Ludwig-Maximilians-Universität München

Direktor: Univ.-Prof. Dr. med. Jens Ricke

# Electrical impedance tomography image reconstruction with structural and multi-scale priors

Dissertation
zum Erwerb des Doktorgrades der Humanbiologie
an der Medizinischen Fakultät der
Ludwig-Maximilians-Universität zu München

vorgelegt von

**Bo Gong**

aus

Shijiazhuang, VR China

Jahr

2018

**Mit Genehmigung der Medizinischen Fakultät der Universität München**

| | |
|---|---|
| Berichterstatter: | Prof. Dr. M.B.A. Gerd Ullrich Müller-Lisse |
| Mitberichterstatter: | Prof. Dr. med. Claus Belka |
| | Priv.-Doz. Dr. Felix Meinel |
| Mitbetreuung durch den promovierten Mitarbeiter: | |
| Dekan: | Prof. Dr. med. dent. Reinhard Hickel |
| Tag der mündlichen Prüfung: | 13. 11. 2018 |

# Eidesstattliche Versicherung

Gong, Bo
______________________________________________________________________

Name, Vorname

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Dissertation mit dem Thema

**Electrical impedance tomography image reconstruction with structural and multi-scale priors**

selbständig verfasst, mich außer der angegebenen keiner weiteren Hilfsmittel bedient und alle Erkenntnisse, die aus dem Schrifttum ganz oder annähernd übernommen sind, als solche kenntlich gemacht und nach ihrer Herkunft unter Bezeichnung der Fundstelle einzeln nachgewiesen habe.

Ich erkläre des Weiteren, dass die hier vorgelegte Dissertation nicht in gleicher oder in ähnlicher Form bei einer anderen Stelle zur Erlangung eines akademischen Grades eingereicht wurde.

| | |
|---|---|
| VS-Schwenningen, 09.03.2018 | Bo Gong |
| Ort, Datum | Unterschrift Doktorand |

## Acknowledgments

First, I would like to express my thanks to Prof. Knut Möller and Prof. Ullrich Müller-Lisse. Their expert guidance and kind support have encouraged me constantly and systematically during the theoretical and practical parts of my Ph.D. study. In particular, I have gained a lot from their professional insight and constructive critique of my scientific research. My sincere gratitude also goes to Prof. Maximilian Reiser from the Institute for Clinical Radiology and Prof. Jens Ricke from the Clinic and Polyclinic for Radiology at the Ludwig Maximilians University of Munich who profoundly supported the cooperation for my research project at the Institute of Technical Medicine of Furtwangen University and provided me the possibility to conduct my Ph. D. study at their institutes.

My appreciation also extends to my colleagues at the Institute of Technical Medicine, Furtwangen University. The family-like environment made the challenging research tasks enjoyable. I always got valuable thoughts from the productive cooperation and constructive discussions with the EIT group members: Dr. Benjamin Schullcke, Dr. Zhanqi Zhao, and Mrs. Sabine Krueger-Ziolek.

I am also grateful to Prof. Marko Vauhkonen and Prof. Gerhard Wolf. Cooperation with them regarding experimental data acquisition and paper formulation were always smooth and beneficial. I am also hugely appreciative to Dr. med. Susanne Nährig and Mrs. Maria Kerscher from the fifth Medical Clinic and Polyclinic (Pulmonology) as well as Priv. Doz. Dr. rer. nat. Rudolf Jörres from the Institute of Occupational Medicine at the Ludwig Maximilians University ofMunich for their steadfast support throughout my Ph. D. research.

Special thanks go to my dearest parents who provide me with endless love and mental support. I feel grateful that they have always encouraged my pursuits and interests.

# Table of contents

# Abbreviations

AAM: artifact amplitude measure

ADMM: alternating direction method of multipliers

ARDS: acute respiratory distress syndrome

BMI: body mass index

CEM: complete electrode model

CF: cystic fibrosis

COPD: chronic obstructive pulmonary disease

CT: X-ray computed tomography

$\Delta I_{left}$(and $\Delta I_{right}$): total conductivity changes corresponding to left and right parts of the reconstructed image

EIT: electrical impedance tomography

FEM: finite element model

$FEV_1$ : forced expiratory volume within one second

$FIV_1$: forced inspiratory volume within one second

FVC: forced vital capacity

GN: Gauss-Newton one step solver with Tikhonov regularization

HU: Hounsfield unit

ICU: intensive care unit

MRI: magnetic resonance imaging

NL: noise level

| | |
|---|---|
| PE: | position error |
| RE: | reconstruction error |
| RES: | resolution |
| RNG: | ring effect |
| SD: | shape deformation |
| SPECT: | single-photon emission computed tomography |
| SSWR: | sparse solver with wavelet-based regularization |
| std: | standard deviation |
| TA: | target amplitude |
| TV: | tidal volume |
| VILI: | ventilator induced lung injury |

# Publication list:

## Selected Journal publications:

**Gong B**, Schullcke B, Krueger-Ziolek S, Vauhkonen M, Wolf G, Mueller-Lisse U and Moeller K (2017). "EIT Imaging Regularization Based on Spectral Graph Wavelets", *IEEE transactions on medical imaging 2017 Sep;36(9):426-436.*

**Gong B**, Schullcke B, Krueger-Ziolek S, Mueller-Lisse U and Moeller K (2016). "Sparse regularization for EIT reconstruction incorporating structural information derived from medical imaging", *Physiological measurement, 2016 Jun;37(6):843-62.*

Schullcke B, **Gong B**, Krueger‐Ziolek S, Tawhai M, Adler A, Mueller‐Lisse U and Moeller K (2017). "Lobe based image reconstruction in Electrical Impedance Tomography", *Medical physics, 2017 Feb;44(2):426-436.*

## Selected Conference publications:

**Gong B**, Schullcke B, Krueger-Ziolek S, Moeller K. EIT reconstruction using higher order TV regularization. 20th World Congress of the International Federation of Automatic Control (IFAC 2017), Toulouse, France.

**Gong B**, Schullcke B, Krueger-Ziolek S, Moeller K. EIT reconstruction regularized by Total Generalized Variation. *18th International Conference on Biomedical Applications of Electrical Impedance Tomography (EIT 2017)*, Hanover NH, USA

**Gong B**, Schullcke B, Krüger-Ziolek S, Möller K. An investigation of the modeling error of linearization for EIT reconstruction. Biomedical Engineering / Biomedizinische Technik 2017, 62(s1)

**Gong B**, and Möller K. Sparse regularization based on spectral graph wavelets. *16th International Conference on Electrical Bio-Impedance (ICEBI) and the 17th Conference on Electrical Impedance Tomography (EIT 2016)*; Stockholm, Sweden

**Gong B**, Schullcke B, Krueger-Ziolek S, Moeller K. EIT image reconstruction based on a clustering dual model framework.. *17th Conference on Electrical Impedance Tomography (EIT 2015),* Neuchatel, Switzerland

**Gong B**, Schullcke B, Krueger-Ziolek S, Moeller K.Improving EIT image reconstruction with clustering. 9th IFAC Symposium on Biological and Medical Systems (*IFAC 2015*) Berlin, Germany

# 1. Introduction

Electrical impedance tomography (EIT) is a radiation-free, real-time imaging technique with promising results in many clinical applications, such as monitoring and evaluating respiratory function, brain nerve activity, intracerebral hemorrhage, and cancer detection (Holder, 2004; Frerichs *et al.*, 2016; Leonhardt and Lachmann, 2012). Unlike other methods, such as CT which investigates X-ray attenuation on different tissues, EIT imaging explores the electrical impedance property of tissues. The physical principle is essentially Ohm's law, which describes the relationship between electrical conductivity, electrical current, and voltage. In EIT, the electrical conductivity distributions are reconstructed from the electrical current and voltage information collected from the electrodes attached to the skin. This regional conductivity information reconstructed from the EIT measurements represents the status of tissues in the same region, hence providing some anatomical and functional insight. Of particular importance is the fact that EIT imaging achieves high temporal resolution, which permits monitoring or analyzing fast physiological processes in real time. Current thorax EIT devices can achieve an imaging frequency of about 40 to 50 images/sec.

However, the spatial resolution of EIT images is low and prone to artifacts, which might lead to misinterpretation of the reconstructed images. Prior knowledge is employed and integrated into the reconstruction procedure to improve the imaging quality. This research considers two different kinds of priors. The first kind (general conditions) assumes that the conductivities of tissues are just smoothly changing in the neighborhood i.e. it is inertial to changes. The second kind of prior (individual conditions) contains structural information which are extracted from patient specific CT images.

# 2. Physical background of EIT

The electrical impedance properties of human tissues have long been employed by researchers to characterize the type as well as the status of human organs. Early attempts were limited to studying the total impedance between two electrodes attached to the skin. However, global impedance information obtained in this way can be quite variable and the measurement data is not straightforward to understand (Kyle *et al.*, 2004). Electrical impedance tomography (EIT) can be considered as an analog to computed tomography (CT) imaging, which uses computerprocessed combinations of X-ray measurements from different angles. By combining many current injection and voltage measurement pairs, images can be obtained which reflect the regional impedance distribution interior of the human body. In this thesis, we focus on EIT experiments within the thorax domain.

A commercially available system (Pulmovista, Draeger Lübeck) requires sixteen electrodes attached equidistantly on a horizontal plane of the thorax. For each pair of neighboring electrodes, electrical currents with a maximum amplitude of 5mA are injected into the tissue. After a short injection period, the next pair of electrodes is selected in clockwise rotation, leading to a total of 16 different current injection locations during one measurement cycle. During every injection period, the induced voltages are measured from the pairs of remaining electrodes. For each current injection, there are 13 pairs of adjacent electrodes and thus 13 independent voltage measurements. Performing 16 current injections in sequential order, 208 voltage measurements can be collected during each measurement cycle. The combination of these 208 different current injection and voltage measurement data is used for EIT image reconstruction. For the sake of modeling convenience, we fix the current injection pattern mentioned above for all further discussions. In this setting, at each point in time, the 208 voltage measurements depend only on the conductivity distribution within the tissue.

## 2.1 Time-Difference EIT

In clinical practice, the changes of conductivity distributions corresponding to two voltage measurement cycles are reconstructed. Such conductivity distribution changes can be reconstructed by using the difference of their corresponding voltage measurements. This strategy simplifies EIT reconstruction by allowing linear approximation of the EIT modeling, which will be discussed in the later part of this thesis. This EIT reconstruction strategy is conventionally called difference EIT. In difference EIT experiments, the voltage measurements are commonly performed continuously in a time interval. A sequence of voltage measurement cycles is collected for EIT reconstruction. An arbitrary cycle can be selected from among these voltage measurement cycles as a baseline voltage measurement. The conductivity distribution corresponding to the baseline voltage measurement is considered as the baseline conductivity distribution. For each voltage measurement cycle, the voltage changes with respect to the baseline voltage measurements can be calculated. The changes of the conductivity distribution with respect to the baseline conductivity distribution can be reconstructed using such voltage changes. A series of images representing the changes of conductivity distribution during the experiment with the same baseline can be obtained.

### 2.2 Functional EIT

The reconstructed series of difference EIT images provides not only information about spatial changes of the conductivity distribution but also about the dynamics of the local conductivity changes over time. Given a thorax EIT image series, the conductivity changes on each pixel over time generate a waveform. This waveform is mainly caused by a periodical ventilation and perfusion process. Each such waveform can be separated into a ventilation part and a perfusion part by applying a frequency filter for the breathing and heart beat frequencies (Frerichs *et al.*, 2016; Frerichs *et al.*, 2009). Conductivity changes can hence be separated into a ventilation part and a perfusion part. So an image series representing the conductivity changes caused purely by ventilation or perfusion can be obtained. More accurate function analysis on ventilation and perfusion can be performed based on such separated data (Frerichs *et al.*, 2009).

## 3. Image Reconstruction

EIT reconstruction is more complex than CT or MRI. For CT and MRI, the regional X-rays or the radio frequency wave signals corresponding to the magnetic resonance propagate straightforward through the human body. In contrast, the injected electrical current spreads within the whole domain and has the inclination to flow along paths with higher conductivities. This makes the reconstruction problem complex to model. Especially the conductivity distribution is highly non-linear with respect to the voltage measurements. Until now, no analytical reconstruction method exists in a closed form.

The EIT reconstruction problem has to be solved numerically. The finite element framework (FEM) is used to discretely represent the thorax by dividing its geometry into non-intersected chambers, which are called finite elements. Using a sufficient number of finite elements so that each finite element can be sufficiently small, it can be assumed that the tissue contained in each element shares the same type and physiological status, hence also the same conductivity. Any conductivity distribution in the human body can be approximated to a predefined degree of accuracy. Intuitively, FEM elements are comparable to pixels of a TV screen. The total number of FEM elements determines the maximum resolution of the approximation of the conductivity distribution.

### 3.1 Numerical Computations

The FEM elements used for the representation of the thorax are tetrahedron elements. Suppose there are sufficiently many such tetrahedron elements, then the conductivity of the tissue covered by each such tetrahedron element can be considered identical. That is, a value can be assigned to each tetrahedron element to represent the local conductivity of the thorax. Collecting all such local conductivity values allows representing the conductivity distribution of the thorax domain. These local conductivity values on tetrahedron elements are the building bricks for EIT modeling and reconstruction. Mathematically, any conductivity distribution within the thorax domain can be written as a vector. Each entry of this vector represents the local conductivity value on a tetrahedron element.

With a fixed current injection pattern, the relation between conductivity distribution and voltage measurement follows Ohm’s law. However, this relation is highly non-linear, hence complex to be applied for EIT reconstruction. Instead, difference EIT reconstruction explores a simpler linear relation between conductivity changes and voltage measurement changes. This linear relation can be explored through simulation using the so-called forward model. Using this linear relation and the known voltage measurement changes between two measurement cycles, the conductivity distribution changes can be solved. This is called an inverse problem.

### 3.2 Forward Model

The forward model studies the correspondence relation between conductivity changes and its induced voltage changes. In difference EIT modeling, we assume that the voltage measurement changes linearly with respect to the conductivity distribution changes which is just approximately correct by assuming the small changes of the conductivity distribution. With the help of the FEM framework, this linear relation can be written as a matrix that maps the vector of the conductivity distribution changes to the vector of the voltage measurement changes. This matrix is called Jacobian matrix. Suppose there are $N$ finite elements in the FEM and $M$ voltage measurements collected during each time measurement cycle, then the Jacobian matrix is an $M \times N$ matrix. Concretely, the $(i, j)$-th entry of the Jacobian matrix saves the linear relation between the conductivity changes on the $i$-th finite element and the voltage changes on the $j$-th voltage measurement.

### 3.3 Inverse Problem and Algorithms

In the forward model, the linear relation between conductivity changes and voltage changes has been described by a Jacobian matrix. Knowing the voltage changes measured by an EIT device and the Jacobian matrix calculated by using simulation, the purpose of solving the inverse problem is to find the corresponding conductivity distribution changes based on this linearity assumption.

Mathematically, this problem is formulated as a set of linear equations. There is one unknown conductivity value associated with each FEM element. Each of these unknown conductivity values is identified as a variable in these equations that needs to be determined. The voltage measurements are the known information in the linear equations. However, the number of voltage measurements is much lower than the number of unknown conductivity variables. That is, voltage measurement is not sufficient for determining a solution of these linear equations; this problem is underdetermined or “ill-posed”.

The insufficient number of independent voltage measurements makes the solution of the linearized inverse problem very unstable. In particular, given the voltage measurement changes, the solution of the inverse problem is not unique. Despite the insufficient number of measurements, in some regions the conductivity changes are hard to notice through voltage changes, for example, the conductivity changes in the center part of the thorax. Physically, this is based on the fact that most of the electrical currents tend to flow around the thorax boundary. The conductivity changes in the center part of the thorax are hence related more weakly to the voltage changes than the conductivity changes around the boundary. The inhomogeneous strength of the relation between conductivity changes and voltage changes leads to large discrepancies between the entries of the Jacobian matrix. This makes the numerical reconstruction unstable. To circumvent this difficulty, researchers are pursuing a stable solution of the linear equations under some prior assumptions. Such prior assumptions confine the flexibility of the solution. These priors are called regularizations for the inverse problem. The whole purpose of EIT reconstruction is to find a conductivity distribution change from the linearized inverse problem constrained with the prior assumptions.

The two most common priors used for EIT reconstructions are Tikhonov (Vauhkonen *et al.*, 1998) and Laplacian regularization (Holder, 2004). Tikhonov regularization assumes that the conductivity changes on each FEM element are very likely around zero. Laplacian regularization assumes the conductivity values on the neighboring FEM elements to be similar and the reconstructed conductivity to be smooth without sharp edges.

# 4. Problem Statement and Goal

The knowledge about priors that constrain the solution space of the inverse problem plays an essential role for the imaging quality. A good prior claims some characteristics of the real conductivity distribution changes to exist, though not known a priori. Reconstructions are enforcing those claimed characteristics in the solution space. The two popular priors mentioned above, which are based on mathematical considerations, are universally applicable for any kind of EIT reconstruction. However, they may be unsuitable in reality for characterizing the conductivity changes for thorax EIT. For thorax EIT, priors representing anatomical and physiological information might be more suitable for reconstruction.

The conductivity changes in the thorax are mainly contributed by ventilation and perfusion in the lung and heart regions. The conductivity changes mainly appear in a sub-region of the thorax domain, hence exhibit a certain spatial sparsity. This physiological prior assumption has been integrated for EIT reconstruction by employing a sparse regularization term in the mathematical formulation of the inverse problem (Jin *et al.*, 2012; M. Gehre, 2012; Javaherian *et al.*, 2015). Reconstructions with sparse regularization detect the region where effective conductivity changes have taken place and set the remaining region to zero. However, images reconstructed under such a sparse prior present spiky artifacts and are unstable when the voltage measurements contain large amounts of noise. The sparse assumption in the prior alone might not be sufficient to characterize the real conductivity distribution changes and to stabilize the reconstruction. This is because in sparse prior assumption, each conductivity value on each FEM element is considered independent of its neighbors. The smoothness of the conductivity distribution is not considered. To introduce smoothness regarding neighboring pixels while at the same time stabilizing the reconstruction under large measurement noise, spectral graph wavelets have been integrated into sparse regularization (Gong *et al.*, 2017).

The anatomical structure obtained from a patient's CT images provides valuable prior information. Tissues belonging to the same anatomical sub-structure can be assumed to have similar electrical characteristics. Consequently, the conductivity distribution changes within each of the sub-structures can be assumed to be similar. According to Schullcke *et al.* (Schullcke *et al.*, 2017), each lung lobe is considered to be one sub-structure. The conductivities of the lung tissue in each lobe are considered to be identical; however, heterogeneity is allowed between lobes. According to this assumption, the flexibility of the solution of the inverse problem can be restricted effectively. Especially the number of unknown conductivity values that need to be determined equals the number of lobes. Because of the low number of unknown parameters, lobe-based reconstruction is fast and is well suited for 3D EIT. The same strategy can be extended to smaller anatomical items, such as lung segments, or sub-segments fed by the same bronchus.

The anatomical structural information can also be combined with the sparsity assumption to construct a structural sparse prior (Gong *et al.*, 2016). The FEM elements in the thorax domain are automatically separated into several clusters according to their structural similarities. Such structural similarities between the FEM elements can be measured based on the geometrical proximity of the FEM elements and their corresponding pixel-intensity information read from the CT image. Intuitively, two FEM elements are more likely to be included in one cluster if they are near each other and share a similar HU value in CT. The conductivity changes are investigated on the cluster level and on the FEM element level. Within each cluster, the conductivity changes are assembled together to represent the conductivity changes of the cluster. The structural sparse prior assumes sparsity on the cluster level. It detects the clusters in which the conductivity shows essential changes. The FEM elements packaged in these clusters are released. The reconstruction of the conductivity distribution changes focuses on these elements. On the one hand, the sparsity on the cluster level reduces the flexibility of the solution of the inverse problem. On the other hand, reconstruction on the released FEM elements shows the conductivity distribution changes on the element level.

# 5. Contributions

1. **GONG B., SCHULLCKE B., KRUEGER-ZIOLEK S., VAUHKONEN M., WOLF G., MUELLER-LISSE U. & MOELLER K. (2017) " EIT imaging regularization based on spectral graph wavelets", IEEE Transactions on Medical Imaging 2017 Sep;36(9):426-436.**

Time-difference EIT reconstructs conductivity changes by using the voltage changes between two measurement cycles. In the thorax, there are regions that present large conductivity changes caused by lung ventilation and perfusion. Tissues in the remaining regions likely exhibit no conductivity changes. Sparse regularization assumes that essential conductivity changes are only present on some FEM elements. Previous studies (Jin *et al.*, 2012; M. Gehre, 2012; Javaherian *et al.*, 2015) have demonstrated that sparse regularization can accurately recover these regions.

Using sparse regularization, the reconstructed image may be corrupted by spiky effects. These spiky effects indicate large differences in conductivity changes between two neighboring pixels. This is not realistic. The neighboring tissues should have greater possibility to share a similar conductivity distribution. Hence, the reconstructed images should present a certain smoothness. These artifacts appear because the conductivity changes on each FEM element are considered independent of those on the neighboring FEM elements. To incorporate smoothness into sparse regularization, we introduce sparse regularization based on wavelets instead of individual FEM elements.

A wavelet can be considered as a local pattern in the thorax domain. Such a pattern is smooth and confined locally to a small circular region. Each wavelet is associated with a center and a scale. The wavelet scale controls the size of the circular region (see Fig. 1 of (Gong *et al.*, 2017)). Some wavelets that share the same center but with different scales are shown in Fig. 1 of (Gong *et al.*, 2017). Any vertex of the triangular FEM elements can be selected as a center of a wavelet. A collection of wavelets is named a filterbank. We introduce a prior assumption that claims that the underlying conductivity distribution change is a weighted superposition of the wavelets in the filterbank. Moreover, we assume the weights used in the superposition are sparse. That is, most of these weights are zero. Because each of the wavelets in the filterbank shows smoothness of the conductivity distribution within a package of neighboring elements, their superposition also provides a certain smoothness. This prior combines sparsity and smoothness.

In (Gong *et al.*, 2017), two types of wavelet filterbanks were used for reconstruction. The first type consists of all wavelets with the same scale. Sparse regularization with such a filterbank can be considered as a smoothed version of sparse regularization. The second type of filterbank consists of wavelets with different scales. This filterbank studies conductivity changes at different scales. In such filterbanks, wavelets with large scales play a role in approximating the rough geometry of the conductivity distribution changes. On the other hand, the detailed structure can be described better if wavelets with smaller scales are used.

Evaluations with Monte Carlo simulations indicate that the proposed solver is more robust to noise and the resulting images show fewer artifacts. This finding is supported by real data analysis. Two lung regions can be clearly divided in the reconstructed image, which can improve the clinical analysis.

2. **SCHULLCKE B., GONG B., KRUEGER-ZIOLEK S., TAWHAI M., ADLER A., MUELLER-LISSE U. & MOELLER K. (2017) " Lobe based image reconstruction in Electrical Impedance Tomography", Medical Physics 2017 Feb;44(2):426-436.**

In this study, patient-specific anatomical information was employed for EIT reconstruction. The anatomical information was obtained from 3D CT scans. Given the thorax CT data, the segmented lung region was divided into five lobe sections. This anatomical lung information was interpreted as a prior to regularize EIT reconstruction. The FEM elements within each lobe were packaged together. Within each lobe, the conductivity distribution change over the FEM elements was forced to be identical and the total conductivity changes of the lobes were studied. This element packaging strategy is based on the assumption that the conductivity distribution change of FEM elements within one lobe region is homogeneous. According to this assumption, the degree of freedom of the underlying conductivity distribution changes can be reduced from thousands to five, which is the number of the lobes. It was further assumed that the voltage changes are all induced by lung ventilation. The reconstruction was only performed on these lobes.

This reconstruction framework was validated by using simulation and clinical experimental data. This method is specially designed for patients with obstructive lung disease, like COPD or CF. Lobe-based analysis of CT scanning has provided valuable information for obstructive lung disease (Kim *et al.*, 2013). The corresponding lung functions on the lobes can be depicted through the conductivity changes obtained by such lobe-based EIT reconstruction.

This lobe-based method was designed and developed by Dr. Schullcke. This author was involved in discussions on some detail techniques and mathematical formulations with him as well as in the review phase of the paper.

3. **GONG B., SCHULLCKE B., KRUEGER-ZIOLEK S., MUELLER-LISSE U. & MOELLER K. (2016) "EIT Sparse regularization for EIT reconstruction incorporating structural information derived from medical imaging", Physiological measurement. 2016 Jun;37(6):843-62.**

In this article, anatomical information has been combined with a sparse prior for EIT reconstruction. The conductivity changes in the thorax are mainly contributed by lung ventilation and perfusion. Tissues belonging to the same organ and being in geometrical proximity are assumed to have similar conductivity distribution changes. The thorax domain has been automatically divided into several blocks. These blocks are obtained by applying a modified k-means algorithm on the FEM elements.

The proposed regularization method integrates this structural information into the reconstruction as a soft constraint, preferring sparsity at the block level. Reconstructions with a structural sparse prior can be viewed as a two-step procedure. First, the reconstruction considers the global effect of each block. In this step, the sparsity assumption helps to the detection of blocks that perform effective conductivity changes. Second, the algorithm releases the FEM elements in the blocks with effective conductivity changes and performs reconstruction on these elements. The conductivity distribution on the FEM level can be reconstructed. Sparsity on the FEM element level is not required.

Structure-based regularization has the potential to balance structural a priori information with data-driven reconstruction. It is robust to noise, reduces artifacts, and produces images that reflect the anatomy and are thus easier to interpret for physicians.

# Summary

Electrical impedance tomography (EIT) imaging achieves high temporal resolution and is radiation-free. With these advantages, EIT has been regarded as a promising technique for lung ventilation and perfusion monitoring. However, the spatial resolution of EIT images is low and prone to artifacts, which might lead to misinterpretation of the reconstructed images. This is mainly because of the two difficulties associated with EIT image reconstruction. One of them is the non-linearity of the physical modeling. The other difficulty regards the insufficient number of independent measurements considering the huge number of unknown parameters.

To improve the imaging quality, prior knowledge has been employed and integrated into the linearized EIT reconstruction framework. Prior knowledge confines the flexibility of the unknown parameters; hence, it effectively reduces the degree of freedom of the reconstruction problem. Unlike some of the canonical priors, which are mainly based on mathematical considerations, two types of priors based on physiological and individual structural information have been developed in a series of studies and are presented in this thesis. The first kind of prior assumes that the conductivities of tissues change only slightly in their neighborhood. Hence the conductivity distribution changes show certain smoothness in geometry. The second kind of prior contains structural information extracted from patient-specific CT images. Such prior knowledge can better characterize the real unknown conductivity changes and lead to a natural restriction of the underlying unknown parameters. Simulation and experimental results indicated that this prior knowledge improved the robustness of EIT reconstruction.

.

## Zusammenfassung:

Die elektrische Impedanztomographie (EIT) ist ein bildgebendes Verfahren, das eine hohe zeitliche Auflösung erreicht und strahlungsfrei ist. Mit diesen Vorteilen wird EIT als vielversprechendes Verfahren zur Lungenventilation und Perfusionsüberwachung angesehen. Die räumliche Auflösung von EIT-Bildern ist jedoch gering und sensitiv gegenüber Artefakten, was zu einer Fehlinterpretation der rekonstruierten Bilder führen kann. Dies liegt hauptsächlich an zwei Problemen bei der EIT-Bildrekonstruktion. Eines davon ist die Nichtlinearität der physikalischen Modellierung. Das andere Problem bezieht sich auf die unzureichende Anzahl von unabhängigen Messungen angesichts der riesigen Menge an unbekannten Parametern.

Um die Abbildungsqualität zu verbessern und zu stabilisieren, werden Vorkenntnisse verwendet und in das linearisierte EIT-Rekonstruktions-Framework integriert. Das Vorwissen beschränkt die Flexibilität der unbekannten Parameter, wodurch der Freiheitsgrad des Rekonstruktionsproblems effektiv reduziert wird. Im Vergleich zu kanonischen Priors, die hauptsächlich auf mathematischen Überlegungen basieren, wurden in einer Reihe von Studien zwei Typen von Priors entwickelt, die auf physiologischen und individuellen Strukturinformationen beruhen und in dieser Arbeit präsentiert werden. Bei der ersten Art wird angenommen, dass sich die Leitfähigkeiten von Geweben in der Nachbarschaft nur leicht ändern, d.h. dass sie inert gegenüber Veränderungen sind. Die zweite Art enthält Strukturinformationen, die aus patientenspezifischen CT-Bildern extrahiert werden. Mithilfe solchen Priors können die realen unbekannten Leitfähigkeitsänderungen besser charakterisiert werden und zu einer natürlichen Beschränkung der zugrundeliegenden unbekannten Parameter führen. Simulation und experimentelle Ergebnisse zeigten, dass dieses Vorwissen eine Verbesserung der Robustheit der EIT-Rekonstruktion zur Folge hatte.

# References:


Frerichs I, Amato M B, van Kaam A H, Tingay D G, Zhao Z, Grychtol B, Bodenstein M, Gagnon H, Böhm S H and Teschner E 2016 Chest electrical impedance tomography examination, data analysis, terminology, clinical use and recommendations: consensus statement of the TRanslational EIT developmeNt stuDy group *Thorax* thoraxjnl-2016-208357

Frerichs I, Pulletz S, Elke G, Reifferscheid F, Schadler D, Scholz J and Weiler N 2009 Assessment of changes in distribution of lung perfusion by electrical impedance tomography *Respiration* **77** 282-91

Gong B, Schullcke B, Krueger-Ziolek S, Mueller-Lisse U and Moeller K 2016 Sparse regularization for EIT reconstruction incorporating structural information derived from medical imaging *Physiological measurement* **37** 843

Gong B, Schullcke B, Krueger-Ziolek S, Vauhkonen M, Wolf G, Mueller-Lisse U and Moeller K 2017 EIT Imaging Regularization Based on Spectral Graph Wavelets *IEEE transactions on medical imaging* **36** 1832-44

Holder D S 2004 Electrical Impedance Tomography: Methods, History and Applications, Institute of Physics *Institute of Physics Publishing* 3-64

Javaherian A, Soleimani M and Moeller K 2015 Sampling of finite elements for sparse recovery in large scale 3D electrical impedance tomography *Physiol Meas* **36** 43-66

Jin B, Khan T and Maass P 2012 A reconstruction algorithm for electrical impedance tomography based on sparsity regularization *International Journal for Numerical Methods in Engineering* **89** 337-53

Kim S S, Seo J B, Lee H Y, Nevrekar D V, Forssen A V, Crapo J D, Schroeder J D and Lynch D A 2013 Chronic obstructive pulmonary disease: lobe-based visual assessment of volumetric CT by using standard images—comparison with quantitative CT and pulmonary function test in the COPDGene study *Radiology* **266** 626-35

Kyle U G, Bosaeus I, De Lorenzo A D, Deurenberg P, Elia M, Gomez J M, Heitmann B L, Kent-Smith L, Melchior J C, Pirlich M, Scharfetter H, Schols A M and Pichard C 2004 Bioelectrical impedance analysis--part I: review of principles and methods *Clin Nutr* **23** 1226-43

Leonhardt S and Lachmann B 2012 Electrical impedance tomography: the holy grail of ventilation and perfusion monitoring? *Intensive Care Med* **38** 1917-29

M. Gehre T K, A. Lipponen, B. Jin, A. Seppänen, J. P. Kaipio and P. Maass 2012 Sparsity reconstruction in electrical impedance tomography: An experimental evaluation *J. Comput. Appl. Math.* **236** 2126–36

Schullcke B, Gong B, Krueger‐Ziolek S, Tawhai M, Adler A, Mueller‐Lisse U and Moeller K 2017 Lobe based image reconstruction in Electrical Impedance Tomography *Medical physics* **44** 426-36

Vauhkonen M, Vadasz D, Karjalainen P A, Somersalo E and Kaipio J P 1998 Tikhonov regularization and prior information in electrical impedance tomography *IEEE transactions on medical imaging* **17** 285-93

# Resume

**Bo Gong**

**bo.gong8432@hs-furtwangen.de**

**+49 17691411487**
**Wannenstr. 27,**

**78056 VS-Schwenningen,**

**Germany**

## Research Experience:

| | |
|---|---|
| Dec. 2014 – present, | Junior Research Scientist, Institute of Technical Medicine, Furtwangen University. |
| 2011 – 2013, | Research assistant, Institute of Manufacturing Metrology, University of Erlangen-Nuremberg. |
| 2011 – 2011, | Research assistant, Institute of Physiology and Pathophysiology, University of Erlangen-Nuremberg. |

## Education:

| | |
|---|---|
| Dec. 2014 – present, | Ph. D. candidate, Institute of Clinical Radiology, University of Munich. |
| 2010 – 2014, | M.Sc., Mathematics and Physics, University of Erlangen-Nuremberg. |
| 2007 –2010, | B.Sc., Mathematics with Computer Science, Technical University of Darmstadt. |
| 2002 – 2007, | B. Medicine, Clinical Medicine, Hebei Medical University, P. R. China. |

# Appendix: Published Journal Articles

1. **GONG B., SCHULLCKE B., KRUEGER-ZIOLEK S., VAUHKONEN M., WOLF G., MUELLER-LISSE U. & MOELLER K. (2017) " EIT imaging regularization based on spectral graph wavelets", IEEE Transactions on Medical Imaging 2017 Sep;36(9):426-436.**

2. **SCHULLCKE B., GONG B., KRUEGER-ZIOLEK S., TAWHAI M., ADLER A., MUELLER-LISSE U. & MOELLER K. (2017) " Lobe based image reconstruction in Electrical Impedance Tomography", Medical Physics 2017 Feb;44(2):426-436.**

3. **GONG B., SCHULLCKE B., KRUEGER-ZIOLEK S., MUELLER-LISSE U. & MOELLER K. (2016) "EIT Sparse regularization for EIT reconstruction incorporating structural information derived from medical imaging", Physiological measurement. 2016 Jun;37(6):843-62.**